



Effective contrast enhancement method for color night vision

Xiaoyan Qian^{*}, Yujin Wang, Bangfeng Wang

College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, 210016 Nanjing, China

ARTICLE INFO

Article history:

Received 30 September 2011

Available online 10 November 2011

Keywords:

Color night vision

Color contrast enhancement

Color transfer

Histogram equalization

ABSTRACT

Image fusion refers to the techniques that integrate complementary information from multiple image sensors' data in a way that makes the new images more suitable for human visual perception. The paper focuses on the low color contrast problem of linear fusion algorithms with color transfer method. Firstly, the contrast of infrared and visible images is enhanced using local histogram equalization and median filter. Then the two enhanced images are fused into the three components of a *Lab* image in terms of a simple linear fusion strategy. To enhance the color contrast between the target and the background, the scaling factor is introduced into the transferring equation in the *b* channel. Experimental results based on three different data sets show that the hot and cold targets are all popped out with intense colors while the background details present natural color appearance. Target detection experiments through target recognition area, detection rate, target-background discrimination also show that the presented method has a better performance than the former methods.

© 2011 Elsevier B.V. All rights reserved.

1. Introduction

The availability of modern night vision systems, like image intensifiers and thermal cameras, enables operations during night and in adverse weather conditions. The two most common night-time imaging systems display either emitted infrared radiation (IR) or dim reflected light. Generally, the visible and IR images are complementary, i.e. the IR image has better hot contrast but less details than visible image, the visible image has much more plenty high-frequency information but worse target contrast especially under bad luminance condition. Thus, techniques for fusing the two images should be employed in order to provide a compact representation of the scene with increased interpretation capabilities. In recent years, fusion of visible and IR images gets increasing concerns. Fusion methods include gray fusion (such as principal component analysis, contrast modulation, pyramid modulation, wavelet transform), and color fusion. In principle, color imagery has several benefits over monochrome imagery for surveillance, reconnaissance, and security applications. The color level which human can distinguish is about hundreds times than gray level and many experiments show that color fusion may improve feature contrast, which allows for better scene segmentation and object detection [1,2]. So color fusion is becoming a more and more important research field and a number of color fusion methods have been proposed [3–6].

One key topic of the color fusion is color constancy. It has been shown that the lack of color constancy with inappropriate color

mapping may hinder human performance [13]. In 2003, Toet [7,8] originally apply color transfer technology that ever been used in color alteration among visible images [9] into multi-band color night vision. This method matches the first order statistical properties (mean and standard deviation) of night vision imagery to those of a target daylight color image. As a result, the color appearance of the colorized night vision image resembles that of the natural target image. But color space transformations between RGB and LMS, LMS and $\tau\alpha\beta$, logarithm and exponent operation occupy much time. And this method does not provide color constancy for dynamic imagery. To overcome above shortcomings, Hogervorst and Toet [2] introduce a simple and fast method to consistently apply natural daytime colors to multi-band night vision imagery. Their idea is easily implemented using standard color lookup table techniques to optimize the match between the false color fused image and the reference image. Once the lookup-table has been derived, the color mapping can be deployed in real-time multi-band image sequences of similar scenes. But this method requires multi-band images and a daytime reference image that are in exact correspondence. And their methods process all three channel of the color space with the same linear mapping in the color transfer step, resulting in low contrast between the target and the background. So targets that are clear in the IR image sometimes may become invisible and are difficult to detect, that may hinder target detection tasks [13].

While popping-out targets is another key topic of color night vision, which enhances human visual capabilities in discriminating features from their background and is essential to target detection tasks. However, to date, little attention has been paid to this problem. In 2007 [10], Wang proposed a nonlinear transfer method

^{*} Corresponding author.

E-mail address: qianxiaoyan@nuaa.edu.cn (X. Qian).

based on local mean value of the IR after nonlinear fusion. This method can pop out the hot targets with intense red color while the background rendered natural color appearance. Zheng [11] and Ma [12] proposed a novel local color night vision algorithm based on image segmentation, recognition and local color transfer to enhance the color mapping effect. However, these methods are even more expensive than Toet's original color transfer [7,8], since they involve time-consuming procedures such as nonlinear diffusion, local recognition, local comparisons and image segmentation. In addition, the nonlinear scheme based on Gaussians convolution operation sometimes brings blur effects. This may hinder situational awareness. In 2010, Yin et al. [13] presented one color contrast enhancement method for color night vision. They introduce a ratio of local to global divergence of the IR image to improve the color contrast in the color transfer process after a simple linear fusion. The experiments show that this method can bring an improvement in the hit rate for target detection than the global statistic method.

But due to the bad weather or environment, the night vision imagery is degraded by the high noise or low contrast, while the above works rarely consider this problem. In addition, Yin's method can get improvement in the target detection, but cold targets are not highlighted effectively and some backgrounds have unnaturally colors in the final fused color image, i.e. road and soil present off-white (seen in Fig. 3c). To get better color night vision effects, here we will present a new simple and effective color fusion method in the *Lab* color space, which can enhance image quality and improve the target detection ability when bringing natural colors. The system is shown in Fig. 1. Based on the existed works, visible and IR images are preprocessed using contrast enhancement and median filter. Consequently, the two enhanced images are fused into the three components of an *Lab* image by means of a simple linear fusion strategy. Different from the global statistic method, the transferring equation in the *b* channel is amended by a scaling factor, which changes according to the distance between the current luminance value and the mean value. In this way the final rendering image has overall clear and natural day-time color appearance when appropriate reference images are selected and the targets are easy to be recognized. This may help observers to improve situational awareness and reduce detection and recognition time.

2. Linear image fusion method

Our fusion approach includes two steps: (1) pre-processing and (2) linear fusion.

2.1. Pre-processing

Visible images captured by charge coupled device (CCD) thermal cameras during night have dark background and low contrast

due to a poorly illuminated environment. Generally most infrared (IR) images brought by thermal radiation have weak details and low contrast due to adverse weather and small temperature difference between target objects and their background. To improve the accuracy of scene recognition, a pre-processing technique is needed before linear fusion.

Histogram equalization (HE) is a simple and effective method of improving the quality of low contrast images that is done by stretching the dynamic range of an image's gray level. HE methods can be divided into two classes: global and local methods. Global HE methods rescale pixel values in an input image (with the size of $M \times N$ and L gray levels) to cover all of the available gray level range by a cumulative distribution function (CDF) t :

$$t = \sum_{i=0}^k \frac{n_i}{n}, \quad n = M \times N, k = 0, 1, \dots, L-1 \quad (1)$$

where n_i denotes the number of the pixels with gray level i .

Global HE is effective in enhancing the low contrast image only if: (a) it contains single object or (b) no apparent contrast change between object and background. While the above conditions cannot be always met, the global methods have both over-enhancement and under-enhancement. Images with extra-high contrast may easily make observer tired and anxious, which are not suitable for long time observation. To overcome these drawbacks, we introduce local histogram equalization (LHE) method into enhancing visible and IR images as following steps:

Step 1: segmenting the input image into several non-overlapping regions with the same size.

Step 2: operating on these regions with CDF, rather than the entire image.

Step 3: the neighboring regions are combined using bilinear interpolation to eliminate artificially induced boundaries. The new value $f'(i,j)$ at position (i,j) is:

$$f'(i,j) = (1-u)(1-v)f(i,j) + (1-u)vf(i,j+1) + u(1-v)f(i+1,j) + uvf(i+1,j+1) \quad (2)$$

where $f(i,j)$, $f(i,j+1)$, $f(i+1,j)$ and $f(i+1,j+1)$ are values before interpolation in the enhancement image, u, v are constant, $u, v \in [0, 1]$.

Step 4: To avoid amplifying noise especially in homogeneous areas in the image, median filtering (MF) is used to smooth the enhancement image which can be described in short:

$$g(i,j) = \text{median}_A \{f'(i-k-l), (k,l) \in A\} \quad (3)$$

where $g(i,j)$ is the median value in the 5×5 neighborhood A around the corresponding pixel $p(i,j)$ in the enhancement result $f'(i-k-l)$ is the gray value of pixels in window A .

2.2. Linear image fusion method

Normally, the false color fused image can be brought by a simple linear fusion scheme mapping the IR and visible image to *R*, *G* and *B* channels. In this paper, we directly obtain the false color image in *Lab* color space in order to speed up this algorithm. Let I_{vis} (visible image) and I_{IR} (IR image) be two input night-vision images with the same spatial resolution and dynamic range.

The false color fused image is given by:

$$\begin{aligned} L &= m_1 \cdot I_{\text{vis}} + m_2 \cdot I_{\text{IR}} \\ a &= I_{\text{vis}} \\ b &= I_{\text{IR}} - I_{\text{vis}} \end{aligned} \quad (4)$$

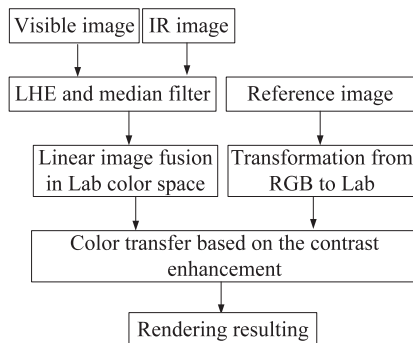


Fig. 1. A typical color image fusion system.

where L represents the lightness value, a and b are chrominance green–magenta and blue–yellow values separately. m_1 and m_2 are constant coefficient ($m_1 + m_2 = 1$), which make the IR and visible images be mapped to the achromatic channel. In this way, we can get a legible back ground because of much details in the visible image is preserved, and in the mean while the targets in the IR image are extruded. In addition, the differencing operation between the visible image and the IR image provides inter-sensor contrast. The resulting image agrees with our natural associations of warm (yellow) and cool (blue). To further enhance the appearance of the fused results, the L , a and b channels can be input to the following remapping stage in which, they can be remapped to alternative “more natural” display.

3. Nonlinear color transfer

The false color fused images of ten have unnatural color appearance and lack of color constancy. In this section, a simple technique is described in order to pop out targets and make the backgrounds full of natural colors. Different from literatures [2,7–13], the color transfer is directly applied to the device independent Lab ($L^*a^*b^*$, CIE1976) color space. And to extrude cold and hot targets, b channel will be enhanced by a scaling factor.

In a color transfer technique, the fused color image should be transformed into a color space with reduced correlation compared to the RGB space. Lab model is a perceptually uniform color space and there is little correlation between the axes; so different operations to different color channels can be applied with confidence that undesirable cross-channel artifacts will not occur. In addition, Lab is the most complete color model used conventionally to describe all the colors visible to the human eye. There is no losing when an image is processed in Lab space.

The first step of the color transfer technique is to transform the RGB tristimulus values of the day-light reference image to device independent XYZ ones as:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.5141 & 0.3239 & 0.1604 \\ 0.2651 & 0.6702 & 0.0641 \\ 0.0241 & 0.1228 & 0.8444 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (5)$$

And then to the Lab color space according to:

$$\begin{cases} L = 116 * f(Y/Y_n) - 16 \\ a = 500 * [f(X/X_n) - f(Y/Y_n)] \\ b = 200 * [f(Y/Y_n) - f(Z/Z_n)] \end{cases} \quad (6)$$

where the opposite colors are on the opposite sides of a line passing through the perfect white tristimulus values X_n, Y_n, Z_n .

In the global color transfer, the three channels are processed with the same linear mapping as following:

$$\begin{cases} L' = \frac{\sigma_{ref}^L}{\sigma_{fuse}^L} (L - \mu_{fuse}^L) \\ a' = \frac{\sigma_{ref}^a}{\sigma_{fuse}^a} (a - \mu_{fuse}^a) \\ b' = \frac{\sigma_{ref}^b}{\sigma_{fuse}^b} (b - \mu_{fuse}^b) \end{cases} \quad (7)$$

From Eq. (7), we can see that the values of each pixel in the fused image are globally modified by the same scaling factor $\sigma_{ref}/\sigma_{fuse}$. Hence, the intensity of the hot and cold targets in IR are weakened, which brings ambiguous targets and will reduce the recognition efficiency. To enhance the contrast between the targets and backgrounds, we propose a nonlinear color transfer scheme which processes each pixel at the basis of luminance distance value in the false color fused image. Because b represents the blue–yellow channel, the larger its value, greater yellow color we can perceive; And the smaller its value, the greater blue color we can perceive. So to pop out hot and cold targets, only the b component in Eq. (7) is needed to be corrected. We modify the color transfer equation with a scaling factor w :

$$b' = w \cdot \frac{\sigma_{ref}^b}{\sigma_{fuse}^b} \tilde{b} \quad (8)$$

And the scaling factor $w(i,j)$ for each pixel (i,j) in the fused image is defined as:

$$w(i,j) = dist(i,j) / <dist> \quad (9)$$

$$<dist> = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N dist(i,j) \quad (10)$$

$$dist(i,j) = \|L(i,j) - <L>\|^p \quad (11)$$

where $dist(i,j)$ denotes the luminance divergence of the pixel (i,j) from the global mean intensity of L channel in the fused image. $L(i,j)$ and $M \times N$ are luminance value of the pixel (i,j) and the size of the fused image separately. p is a constant that can be modified according to the actual requirement for the enhancement. When p is set as 1, it become Yin's method, so Yin's method is only special case of our method. The effectiveness of color contrast enhancement become better along with the increasing of the parameter p in a certain range. In this way, the intensity of each pixel in the IR image can be expressed in the colorized result. And meanwhile the global transfer method brings the natural colors. Finally, we convert the result back to RGB.

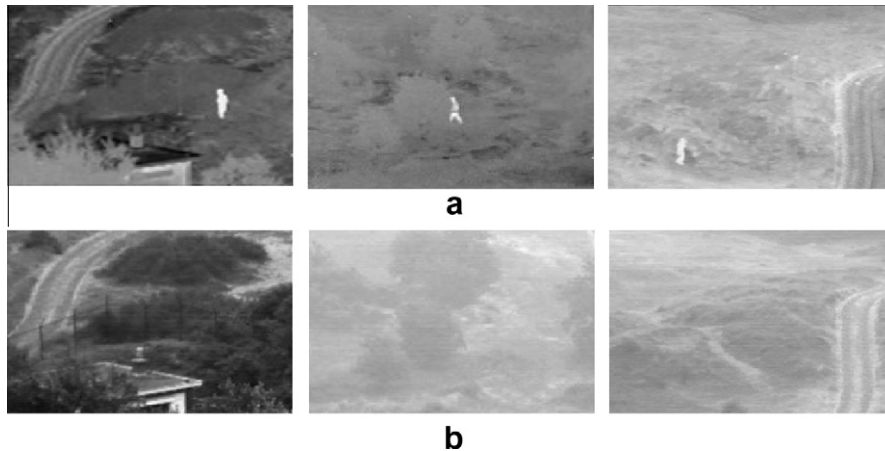


Fig. 2. Three sets of night-time images: (a) IR images and (b) visible images.

4. Colorizing results

To validate the effectiveness of our method, three image sets are fused. For comparison, we also obtain the color fused images by Toet's method without enhancement [7] and by Yin's enhancement method [13]. The three image sets are shown in Fig. 2. Fig. 2a is IR images and Fig. 2b is corresponding visible images.

Fig. 3 is the comparing experiment among our method, Toet's and Yin's methods. Fig. 3b–d are the colorizing results brought

by Toet's global statistic method, Yin's method in YUV space without pre-processing and our method separately. It can be seen that the man takes on almost the same colors as the background and is very difficult to be detected without contrast enhancement and pre-processing in Fig. 3 b. But the man can be popped out using Yin's and our methods. The man appears intense red in Fig. 3 c and intense yellow in Fig. 3d. When comparing with Yin's method, tests show that both hot and cold targets are more outstanding in our rendering result. The man become bigger and brighter in

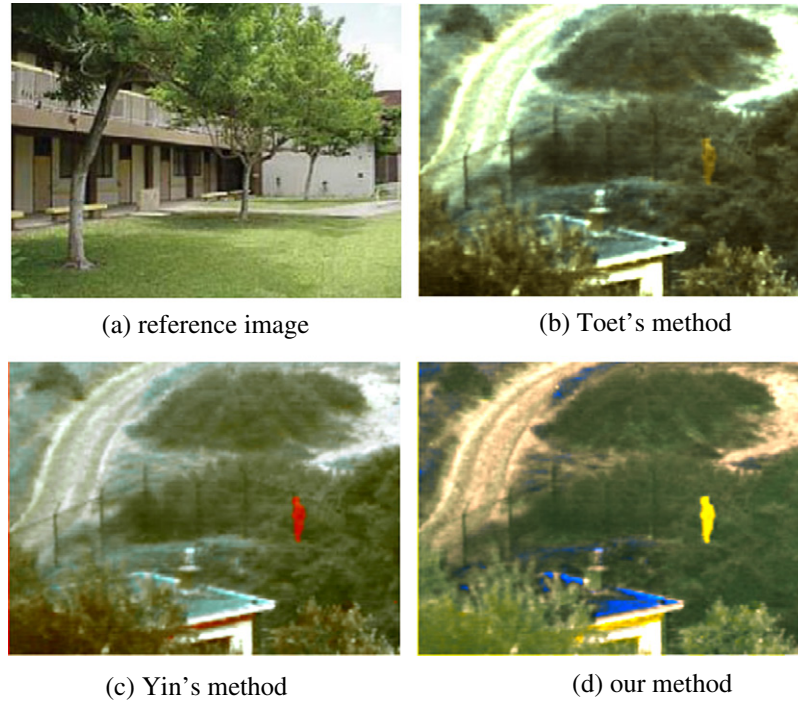


Fig. 3. Fusion experiment of image pair NV1816.

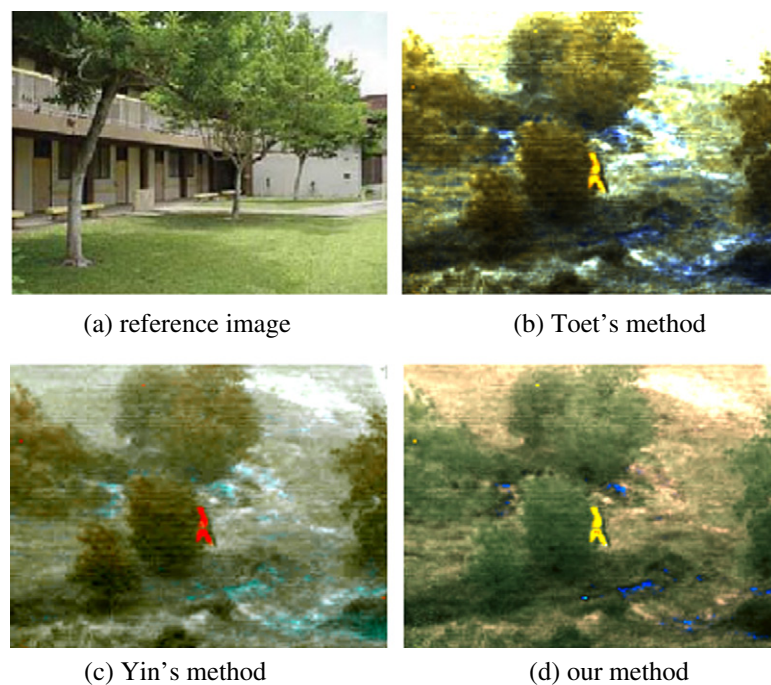


Fig. 4. Fusion experiment of image pair NV4917.

Fig. 3d. The cold targets such as the roof present light cyan in Fig. 3c, yet they obviously present deep blue in Fig. 3d. In addition, the details are clearer and the backgrounds can present more natural colors in our result. The trees are green and the soil takes on suntan in Fig. 3d. While there are some red colors in the bottom of the Fig. 3c and the soil presents bright white using Yin's method. The reason is that *Lab* have much broader color range than other color spaces. There is no losing when an image is processed in *Lab* space. And local histogram equalization and MF can eliminate noises and improve the image contrast.

The same conclusions can be deduced from experiments using NV4917 pairs and NV7404 pairs (seen in Figs. 4 and 5). Without

pre-processing and channel's enhancement the man is hard to distinguish from the background (e.g. Figs. 4b and 5b). Yin's and our methods provide better results (seen in Figs. 4 and 5c and d). The man appears red and intense orange–yellow, thus can be easily distinguished from the backgrounds.

5. Discussions

Human visual inspection will be a good choice to evaluate colorized images. However, the reproduction of subjective tests is often time-consuming and difficult, while the exact same conditions

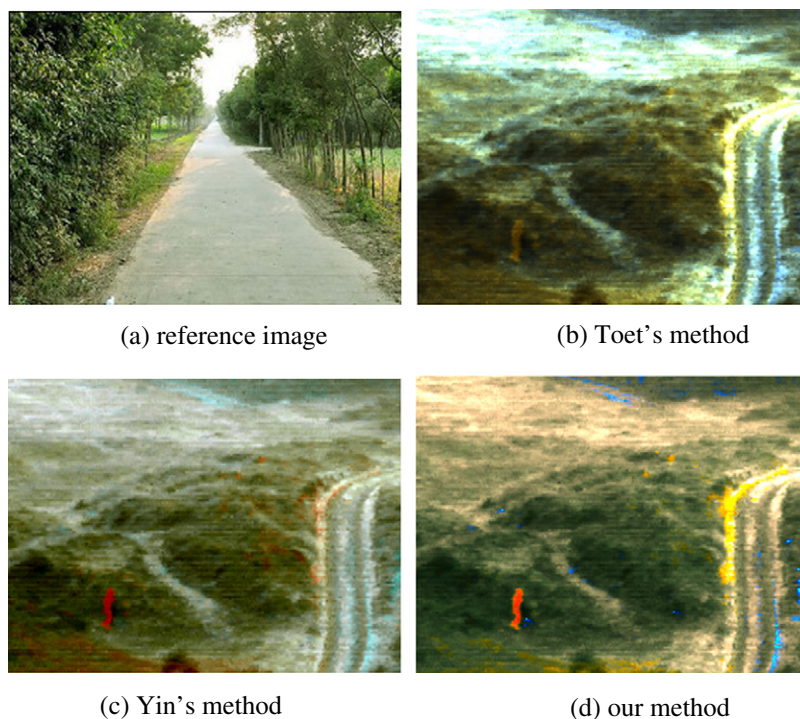


Fig. 5. Fusion experiment of image pair NV7404.

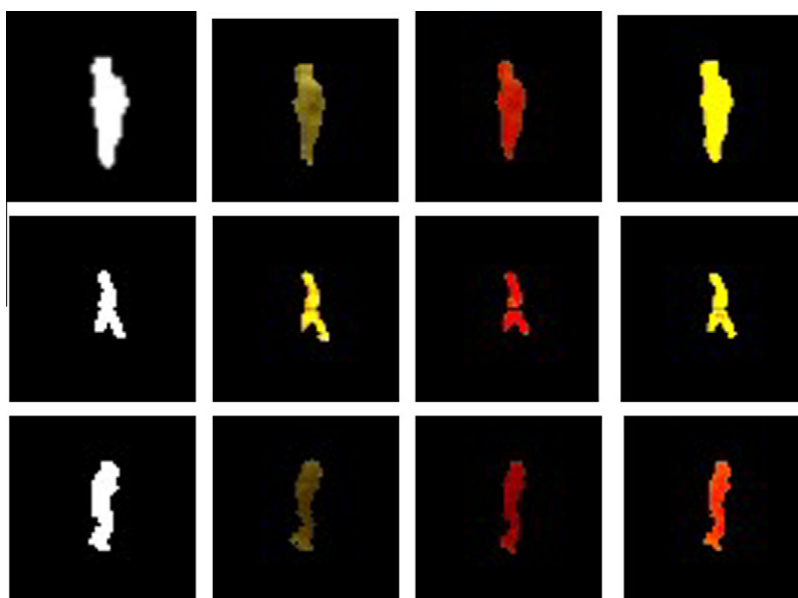


Fig. 6. Detection results of different methods.

for the test cannot be guaranteed. Unfortunately, there is no effective and well-accepted objective metric for color fusion schemes. However, as we aim at improving the identification ability of the targets by pre-processing and enhancing methods, we can roughly evaluate different color fusion methods through their detect abilities of the target [13]. Before giving the evaluation metrics, one precondition is to know the ideal target detection result, which is obtained manually from IR images in this paper. For color fusion images, we first produce different color fields by K-means clustering, then adopt threshold segmentation to extract targets. In the case of Figs. 3–5, man is the observed hot target. The images in Figs. 6 are the segmented results of the above datas respectively. The first columns are the ideal targets. The detection results of Toet's, Yin's and our methods are shown from the second to the fourth columns.

Then we evaluate different methods by calculating target's recognition area, detection rate, target-background discrimination. The recognition area s can be defined as the total number of pixels over the target field. The detection rate $rate$ is described as:

$$rate = \frac{num_{correct}}{num_{ideal}} \quad (12)$$

where $num_{correct}$ denotes the sum of pixels detected correctly in the fused image, that is to say the corresponding pixels in the detected target to those in the ideal target. num_{ideal} is the total number of pixels in the ideal target.

The parameters S and $rate$ only evaluate the targets detection ability from target itself, while they cannot embody the difference between the target and the background. When the target's colors are very close to those of its surrounding background, it is difficult to distinguish although the detection rate may be large. So we also roughly evaluate different methods through their target-background discrimination described by receiver-operator-characteristic (ROC) curves and color distance between the target and the background.

A ROC curve is a plot of false alarm rate versus detection rate, calculated by determining what fraction of pixels are above and below varying threshold levels in HSV color space [14]. To obtain ROC curves, we first transform the color fused results from RGB color space to HSV space. Then target detection is performed through the hue and saturation components:

$$tar(x,y) = \begin{cases} 1 & |H(x,y) - \tilde{H}| \leq H_T \text{ and } |S(x,y) - \tilde{S}| \leq S_T \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

where $tar(x,y)$ is the target detection result; $H(x,y)$ and $S(x,y)$ are the hue and saturation components of the color fused image at the coordinate (x,y) , respectively; $\tilde{H}$ and $\tilde{S}$ are the mean values of the hue and saturation of the target brought by K-means clustering, respectively; H_T and S_T are some given hue and saturation thresholds.

Then the false alarm rate $rate_{false}$ can be defined as:

$$rate_{false} = \frac{num_{false}}{all - num_{ideal}} \quad (14)$$

Where num_{false} denotes the sum of the pixels belonging to the background and they are looked as the target by mistake using Eq. (13). all is the total number of the pixels in the color fused image. The

ROC curves can be obtained with varying false alarm rates and target detection rates brought by different hue and saturation thresholds for the target detection.

Table 2

Comparisons of recognition area and detection rate for different methods.

	S_{ideal}	S_{glo}	S_{yin}	S_{our}	$rate_{glo}$ (%)	$rate_{yin}$ (%)	$rate_{our}$ (%)
Fig. 3	242	183	198	237	75.21	81.82	97.11
Fig. 4	113	100	85	101	84.96	75.22	89.38
Fig. 5	180	171	138	135	89.44	76.67	75.00

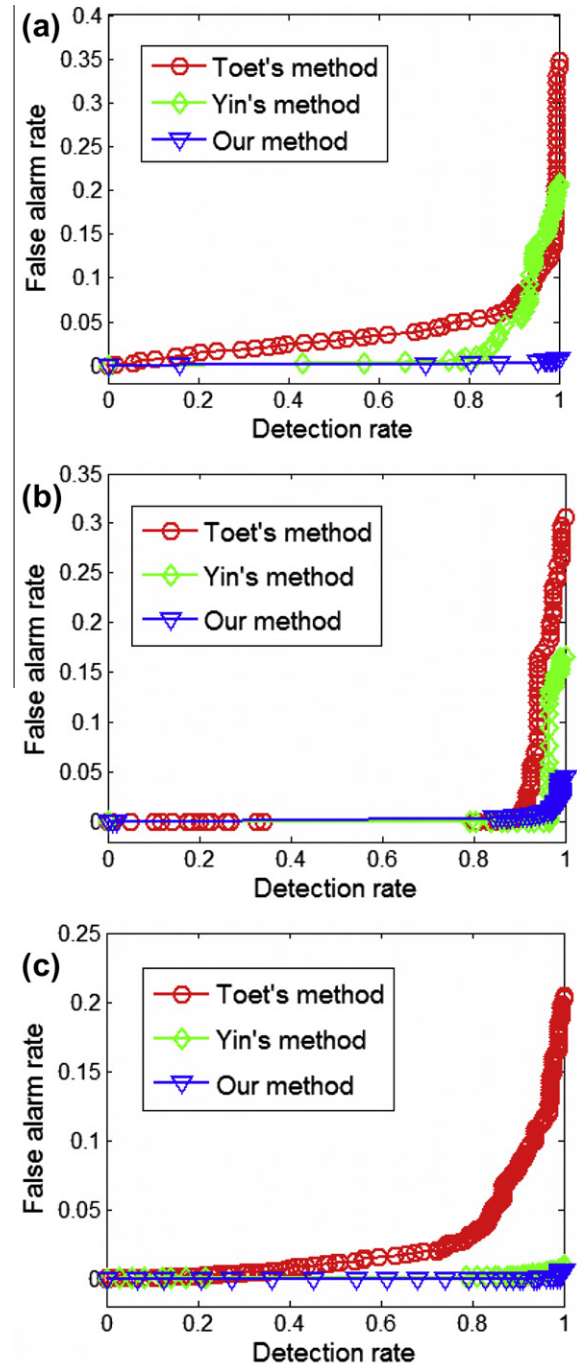


Fig. 7. ROC curves for the target-background discrimination with different image fusion methods: (a) ROC curves for the color fused results of image pair NV 1816; (b) ROC curves for the color fused results of image pair NV4917; (c) ROC curves for the color fused results of image pair NV7404.

Table 1
Parameters setting for three sets.

	m_1	m_2	Clustering number	p
Fig. 3	0.5	0.5	7	3
Fig. 4	0.35	0.65	7	5
Fig. 5	0.7	0.3	7	6

Table 3

Comparisons of region size color distance for different methods.

	Region size	D_{glo}	D_{Yin}	D_{our}
Fig. 3	90 × 110	31.32	67.68	81.78
Fig. 4	90 × 110	22.24	68.86	75.48
Fig. 5	90 × 110	21.57	63.43	80.62

Table 4

Comparisons of full size color distance for different methods.

	Full size	D_{glo}	D_{Yin}	D_{our}
Fig. 3	277 × 209	31.65	69.82	78.45
Fig. 4	208 × 105	20.79	69.40	73.90
Fig. 5	280 × 209	34.72	74.06	77.28

The hit rate of color vision in detecting a target relies mainly on its ability to characterize color [15]. When the target is far from the background in color, it improves the object-background discrimination. So we measure the color distance between the target region and its surrounding region. The distance D is defined as the Euclidean distance in Lab color space:

$$D = \sqrt{(\langle L_t \rangle - \langle L_b \rangle)^2 + (\langle a_t \rangle - \langle a_b \rangle)^2 + (\langle b_t \rangle - \langle b_b \rangle)^2} \quad (15)$$

where t, b stand for the target and the background regions, respectively. $\langle \rangle$ is the mean value.

Table 1 is the parameters setting for the three sets. They are the empirical values brought by several experiments. Table 2 shows the comparisons of recognition area and detection rate for different methods. The first column is the ideal target's area. S_{glo} , S_{Yin} and S_{our} denote the target's area of Toet's colorizing method, Yin's and our methods separately. And the next three columns give the detection rate of the three methods. Yin's method enlarges the recognition area and improves the detection rate comparing with Toet's global method, while the two parameters provided by our method are much closer to the ideal value, resulting in a performance improvement. We also see that the recognition area and detection rate are not very ideal from the third set (Fig. 5), because the parameter p has a larger value than that in Figs. 3 and 4. The larger is the parameter p , the more obvious the targets are. But the recognition area will be smaller.

Fig. 7 gives the ROC curves for different methods. The varying hue and saturation thresholds are increased by step-length 0.005. It can be easily seen that the proposed method provides an improvement for target-background discrimination, as for the same false alarm rate, it obtains a higher detection rate.

Tables 3 and 4 shows the comparisons of color distances in Lab space. Table 3 is the local comparison and the region size is 90 × 110. Table 4 gives the global comparison for different methods. Yin's method enlarges the distance between the target and the background drastically due to the intense red colors of the targets. While our method shows better performance from local and global comparisons. The color distance between the targets with the intense yellow colors brought by our method and the backgrounds has three to four times than that of Toet's global method

without channel's contrast enhancement. It also can be seen that the color distance brought by our method also gets improvement comparing to that of Yin's. Besides, our method raises the target's recognition area and detection rate seen from Table 2.

6. Conclusions

In this paper, we discuss a simple and effective color contrast enhancement method for color night vision. Before fusion, local histogram equalization and median filter are introduced to improve the visible and IR images' quality. Then a simple linear fusion method is proposed. In order to get natural colors and improve the target detection ability, an amended global color transfer method is applied. Under the control of the scaling factors, the targets can be popped out and meanwhile the backgrounds are rendered with natural colors. Visual experiments and object metrics all show that our method has a better performance.

Acknowledgements

This study is supported by China Postdoctoral Science Foundation (Grant No. 20110491415) and Technology Project of Civil Aviation Administration of China (Grant No. MHRD201124). Many thanks to Alexander Toet and TNO Human Factors Research Institute for providing the source IR and visible image sequences that are publicly available online at <http://www.imagefusion.org>.

References

- [1] G.L. Walls. The vertebrate eye and its adaptive radiation, Granbrook Institute of Science, Bloomfield Hills, Michigan, 2006.
- [2] M.A. Hogervorst, A. Toet, Fast natural color mapping for night-time imagery, Information Fusion 11 (2010) 69–77.
- [3] E.A. Essock, M.J. Sinai, J.S. McCarley, W.K. Krebs, J.K. DeFord, Perceptual ability with real-world nighttime scenes: image-intensified, infrared, and fused-color imagery, Human Factors 41 (3) (1999) 438–442.
- [4] A.M. Waxman et al., Solid-state color night vision: fusion of lowlight visible and thermal infrared imagery, MIT Lincoln Laboratory Journal 11 (1999) 41–60.
- [5] D.A. Fay, A.M. Waxman, M. Aguilar et al., Fusion of 2-/3-/4-sensor imagery for visualization, target learning and search, in: Proceedings of SPIE, Enhanced and Synthetic Vision 2000, vol. 4023, Orlando, FL, 2000, pp. 105–115.
- [6] A.M. Waxman, A.N. Gove, D.A. Fay, J.P. Racamoto, J.E. Carrick, M.C. Seibert, E.D. Savoye, Color night vision: opponent processing in the fusion of visible and IR imagery, Neural Networks 10 (1) (1997) 1–6.
- [7] A. Toet, Natural color mapping for multiband nightvision imagery, Information Fusion 4 (2003) 155–166.
- [8] A. Toet, Color the night: applying daytime colors to nighttime imagery, Proc. SPIE 5084 (2003) 68–178.
- [9] E. Reinhard, B. Gooch, et al., Color transfer between Images, IEEE Computer Graphics and Applications 21 (5) (2001) 34–41.
- [10] L.X. Wang, S.M. Shi et al., Color fusion algorithm for visible and infrared images based on color transfer in YUV color space, Proceedings of the SPIE-The International Society for Optical Engineering, 2007, v 6787 n1: 67870S-1-7.
- [11] Y. Zheng, E.A. Essock, A local-coloring method for night-vision colorization utilizing image analysis and fusion, Information Fusion 9 (2) (2008) 186–199.
- [12] S. Ma, J.A. Fang, S.Y. Sun, et al., Colorizing algorithm of night-vision image based on clustering of false color fused image, Acta Optica Sinica 29 (6) (2009) 1502–1507.
- [13] S.F. Yin, L.C. Cao, Y.S. Ling, et al., One color contrast enhanced infrared and visible image fusion method, Infrared Physics and Technology 53 (2010) 146–150.
- [14] D. Scribner, P. Warren, J. Schuler, Extending color vision methods to bands beyond the visible, Machine Vision and Applications 11 (2000) 306–312.
- [15] K. Lee, W. Daley, Q. Li, Artificial color contrast for machine vision and its effects on feature detection, Proceedings of SPIE MB4-03 (2005) 225–249.